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Article

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Review

# Communicating complex ecological models to non-scientist end users

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Complex computer models are used to predict how ecological systems respond to changing environmental conditions or management actions. Communicating these complex models to non-scientists is challenging, but necessary, because decision-makers and other end users need to understand, accept, and use the models and their predictions. Despite the importance of communicating effectively with end users, there is little guidance available as to how this may be achieved. Here, we review the challenges typically encountered by modellers attempting to communicate complex models and their outputs to managers and other non-scientist end users. We discuss the implications of failing to communicate effectively in each case. We then suggest a general approach for communicating with non-scientist end users. We detail the specific elements to be communicated using the example of individual-based models, which are widely used in ecology. We demonstrate that despite their complexity, individual-based models have characteristics that can facilitate communication with non-scientists. The approach we propose is based on our experiences and methods used in other fields, but which until now have not been synthesised or made broadly available to ecologists. Our aim is to facilitate the process of communicating with end users of complex models and encourage more modellers to engage in it by providing a structured approach to the communication process. We argue that developing measures of the effectiveness of communication with end users will help increase the impact of complex models in ecology.



**Contents**



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## 1. Complex ecological systems call for complex models

Ecological systems are experiencing a period of pervasive and unprecedented rapid change (Reid et al., 2005). To decide how to manage them appropriately we need the ability to predict how they will respond to different management actions (Evans, 2012). Traditional phenomenological models (i.e. descriptive or correlative models) can be too simplistic to use for prediction because they are limited to the specific local context for which there is already empirical data (Stillman et al., 2015). To capture the complexity and variability of ecological systems, we can use computer simulation models, such as process-based or individual-based models (IBMs; also known as agent-based models; Railsback and Grimm, 2011). Such models simulate a complex system by specifying the processes that characterise interactions between its individual parts. IBMs in particular work on rules that direct the behaviour of individuals in a model population. The population's dynamics emerge during the IBM simulation (Grimm and Railsback, 2005) and these emergent patterns are then compared with empirical data to test the credibility of the model. If the model produces realistic patterns it can be used to predict system dynamics in novel environments, beyond the conditions for which there is already data.

IBMs have been used in ecology for 40 years (DeAngelis and Grimm, 2014) and are increasingly being used as practical tools in contexts such as wildlife conservation (McLane et al., 2011), ecosystem restoration (Darby et al., 2015; Fitz, 2015; Orem et al., 2014), agro-chemical risk assessment (Forbes et al., 2009; Topping et al., 2015), fisheries management (Rose, 2000) and assessing the wildlife impact of renewable energy developments (Nabe-Nielsen et al., 2014 Stillman and Goss-Custard, 2010). They have several advantages over phenomenological models in such contexts (Table 1), including the ability to predict the consequences of different management scenarios, so that decision-makers can visualise the outcomes of alternative courses of action. Despite such advantages however, the complexity of IBMs and other similarly complex models can make it difficult to communicate the underlying drivers, and the precision and credibility of the predictions. These elements are important for achieving end-user acceptance and correct application of the predictions in operational contexts.

Here, we identify the main challenges and suggest an approach to communicating complex ecological models to non-scientist end users. We provide examples for IBMs, although the issues we highlight and the approach we suggest are relevant to most applied ecological models. We draw together the experiences of modellers working in a variety of applied contexts, including ecological risk assessment, multi-species fisheries and conservation.

## 2. The need to communicate with end users

Communication of complex models is needed to help incorporate scientific evidence into environmental decision making (DeFries et al., 2012; Walsh et al., 2015). Model outputs are used to identify and prioritise management options (e.g. Elmeros et al., 2015 based on Topping et al., 2003; Hyder et al., 2015), to provide an evidence base to inform decision-making, and an audit trail for inspection (Dicks et al., 2014). They must therefore be conveyed to end users so that they are understood and interpreted unambiguously (Fig. 1). Model outputs of key interest normally include predictions of emergent system dynamics for a particular scenario, but also measures of precision and uncertainty that enable the predictions to be understood in context, interrogated, and believed. The end users ('stakeholders') of these outputs can be decision- or policy-makers, risk assessors, regulators and resource managers, who are often non-scientists and/or non-specialists (which in this context are comparable).

There is no broadly accepted procedure for communicating complex ecological models to stakeholders, even though the need for better science communication in general is well-recognised (Fischhoff and Scheufele, 2014) and actively addressed in other fields such as climate science (Kreienkamp et al., 2012; Stephens et al., 2012), fisheries management (e.g. the GAP2, project: http://gap2.eu) and risk assessment (Hunka et al., 2013). This lack of guidance and structure in planning and carrying out communication could limit the effectiveness of complex models in ecological decision-making (Addison et al., 2013), allow a knowledge gap to develop between modellers and practitioners, and reduce the societal impact and relevance of the research (Shanley and López, 2009). To help provide much-needed guidance, we offer a systematic approach to communicating complex models to non-scientist stakeholders based on theory, author experience and examples of good practice.

## 3. Guidelines exist for communicating with fellow modellers

In recent years, approaches have been suggested that aim to standardise the development and documentation of complex models. This has improved communication amongst modellers, facilitated critical scientific evaluation, and helped to ensure that models can be fully checked and re-implemented if necessary in alternative computer languages or platforms. Pattern-oriented modelling (POM) provides a unifying framework for IBMs (Grimm and Railsback, 2012), the 'ODD' (Overview, Design, concepts and Details) protocol (Grimm et al., 2010, 2006) and 'transparent and comprehensive ecological modelling' (TRACE) documentation (Grimm et al., 2014) help standardise model documentation, 'evaluation' (Augusiak et al., 2014) is a framework for assessing model quality and reliability, and approximate Bayesian computation (ABC) is a method of objectively evaluating and calibrating complex stochastic models (Beaumont, 2010; van der Vaart et al., 2015). These approaches largely focus on the technical details of modelling and by structuring the modelling and reporting ultimately facilitate communication. Generally, however, they present communication of the model outputs to stakeholders as an explicit step in the modelling cycle and provide no specific guidance on how it should be done. We argue that communication should constitute

**Table 1**
Advantages of individual-based models over phenomenological models when communicating with non-scientist end users.

| IBM Attribute | Advantage |
|---|---|
| 1. Based on first principles | IBMs are founded on basic principles such as that individuals seek to maximise fitness. |
| 2. The individual is the basic unit | The behaviour of individual organisms is often easier to comprehend than entire populations. |
| 3. Simple rules are applied to individuals | Population-level dynamics emerge from localised decision-making processes, which in turn are based on simple rules driving individual behaviour. |
| 4. Real world relevance | IBMs are more like real organisms and environments than classical population models because they are based on individuals living in mapped environments in which resources vary with time. |
| 5. Complexity is included, not averaged away | The model can incorporate all relevant complexity including heuristic knowledge of stakeholders. |
| 6. Less abstract assumptions | IBMs are based on concrete mechanisms and their assumptions are less abstract than those of classical population models. |
| 7. User-friendly software | Packages such as *NetLogo* enable ecologists without programming expertise to create IBMs (for a software review see Nikolai and Madey 2009) and enable stakeholders to check, interrogate, visualise, share and interact with the model. |
| 8. Visualisations are easy to produce | The behaviour of individuals over time and space can be viewed in dynamic visualisations, helping to communicate what the model is doing. |
| 9. Insight into state of individuals | IBMs can reveal the state of individuals in a population as well as the population itself, adding another dimension to the understanding about the system. |
| 10. Multiple levels of validation | Submodels as well as the final model are tested and evaluated using multiple data sets, helping to build stakeholder confidence in the validation process. |

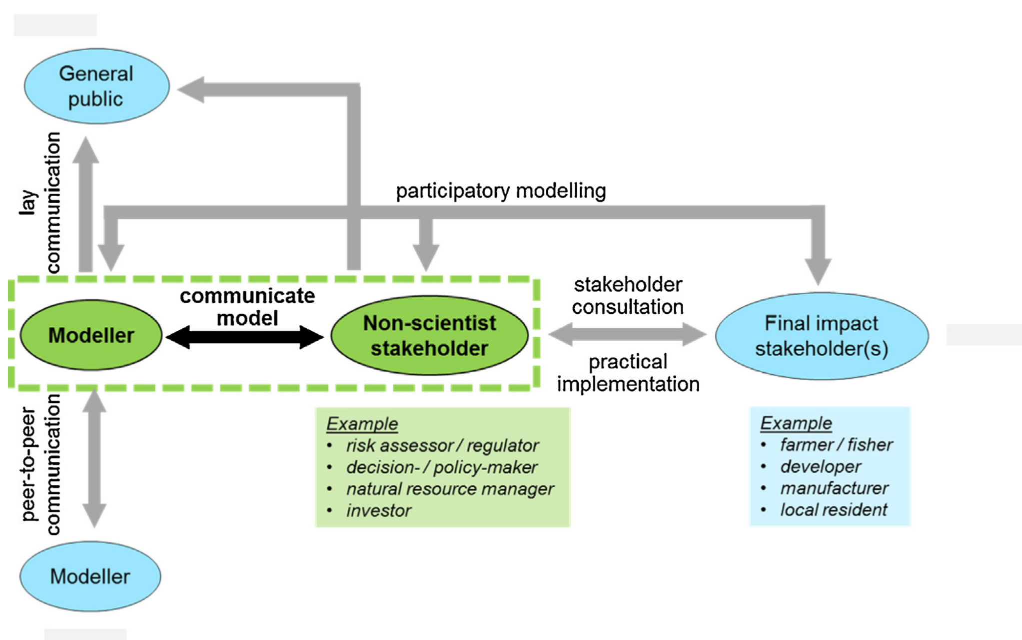


**Fig. 1.** The applied science communication landscape. The area enclosed by dashed green lines indicates the focus of this article. Little formal guidance is available for this communication interface. A subsequent communication interface occurs between non-scientist stakeholders and those termed 'final impact' stakeholders (individuals affected by the decisions made using scientific evidence), for which guidance is available elsewhere (Reed, 2008). Arrows indicate the direction of information flow.

an integral part of the iterative model development process (Fig. 2) rather than a one-way transmission of information at some point during a project.

## 4. Challenges to effective communication

Communicating complex ecological models to stakeholders poses multiple challenges. These can be categorised into two stakeholder-focussed challenges: (i) political context and (ii) stakeholder experience; and three practical challenges: (iii) model characteristics, (iv) conveying uncertainty, and (v) the form of communication required by stakeholders. We deal with each in turn.

### *4.1. Political context*

The modeller's approach to communicating a complex model depends on its real-world application. When important decisions are at stake, the modelling process itself can become politicized. Similarly, highly politicized contexts (e.g. the role of badgers in the spread of bovine tuberculosis amongst cattle in the UK (Woodroffe, 2015), or the impact of neonicotinoid pesticides on bee populations and arable yield (Dicks, 2013)) require careful communication to maximise stakeholder trust and understanding of the results, while minimising misinterpretation. In polarised debates, stakeholders often come from opposing sides, have multiple sources of information and culturally-formed ideological biases in their interpretation of the issue (Kahan et al., 2011). Entrenched opinions can lead to a bi-stable response whereby stakeholders either believe model outputs uncritically ('blind faith'), or completely reject the simulation results. In the former scenario, the risk is that stakeholders implicitly believe the model without understanding its uncertainties and limitations, paying attention to only the main result without critically assessing the method. Ultimately this might result in poor decisions being made if model outputs are trusted beyond the domain of the model's validity. On the other hand, stakeholders refusing to accept simulation results that contradict their point of view present an additional problem: to what extent is it the modeller's responsibility to fully engage this type of stakeholder and

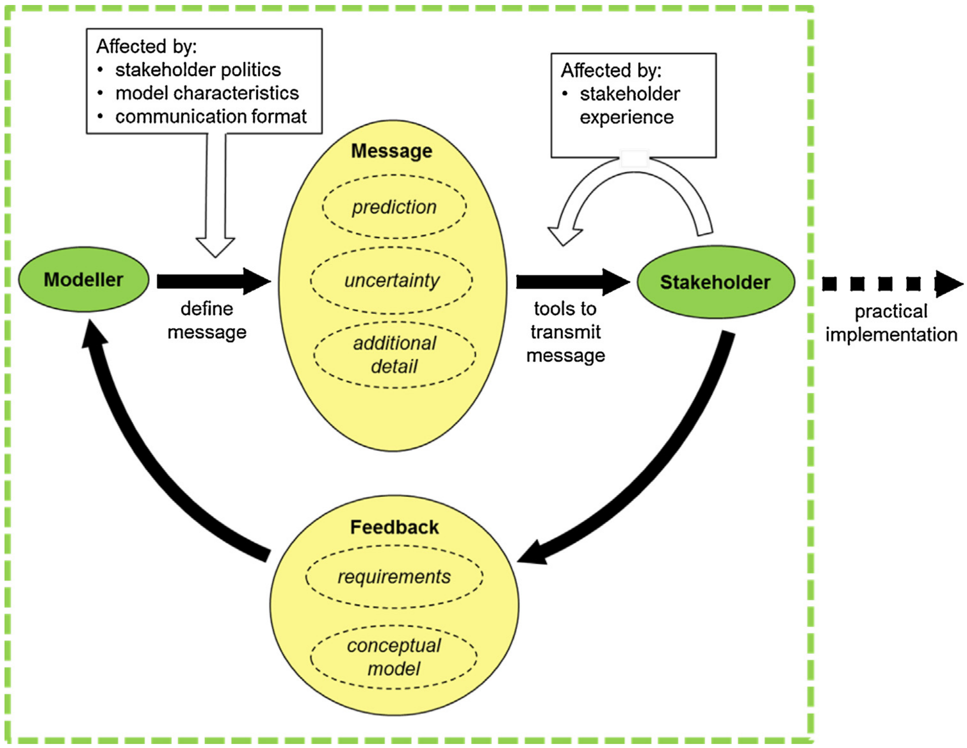


**Fig. 2.** Communication within the modelling cycle. Elements involved in communicating complex ecological models to non-scientist stakeholders. The modeller initially defines the message to be communicated. Essential components of this message include the model prediction and associated uncertainty. Message complexity will depend on the context, model and method of communicating. Communication tools might include visualisations and real-time use of model graphical interfaces. Both before and after the message is conveyed, the stakeholder may indicate to the researcher what their information requirements are, which can inform overall model design.

ensure model results are incorporated into the decision-making process (Pielke, 2007)?

### 4.2. Stakeholder experience

Stakeholders range in both their level of technical understanding and their experience of using the outputs from complex models in decision-making. As a result, they can have pre-existing ideas about computer simulations as opposed to the 'real world' of empirical data, and will differ in their practical requirements for receiving information about the model and its outputs.

For instance, some stakeholders may prefer familiar, simple mathematical models that are inappropriate for prediction but widely employed because non-scientists can understand them. As an example, an aquatic habitat model, 'PHABSIM', that has been contentious for more than 20 years is still used to guide resource management despite the existence of suitable, reliable IBMs (Lang, Railsback and Associates, 2000). Some stakeholders may be inherently sceptical of predictions arising from complex models, particularly if the output of these contradicts current opinion or practice, or appears superficially counterintuitive. Similarly, some stakeholders may refuse to trust anything from a complex model, wrongly believing that the uncertainty of predictions always increases with model complexity. They may be unwilling to learn enough about a complex model to understand the true degree of uncertainty and focus only on details with which they are familiar, quibbling unnecessarily over which processes are, or are not, included in the model.

Alternatively, some stakeholders may assume the model is too complicated to understand, observing only the headline results. The danger here is that the stakeholders offer only limited critical insight and any relevant knowledge they might have cannot be accessed or utilised in model revisions. Likewise, there are stakeholders who may mistakenly assume a complex model is a complete representation of the real world rather than a tool to simulate key processes and test hypotheses that cannot easily be tested in laboratory or mesocosm conditions. In these cases, there is a risk that the model outputs will be trusted uncritically and interpreted incorrectly. The challenge for the modeller is to achieve the middle ground; informed acceptance of model outputs.

Stakeholders who are routinely exposed to complex models, either because their subject area is well-modelled, or because their professional role involves established communication channels between modellers and stakeholders (e.g. in industry and advisory bodies), will be accustomed to technical descriptions and require a succinct approach in a familiar format enabling information to be delivered, understood and acted upon rapidly.

### 4.3. Model characteristics

System and model complexity will affect the communication approach. For example, single species models (e.g. Johnston et al., 2014) addressing simple systems may be easier to communicate than multi-species, multi-trophic models (e.g. Harfoot et al., 2014) that address multi-dimensional problems. Generally speaking, models should not be too complicated or too simple for their intended use (Addison et al., 2013). A modeller can easily fall into the trap of putting 'everything' into the model, or passively accept a gradual ratcheting-up of model complexity as a result of peer pressure to have a more comprehensive model, which superficially may appear more credible. There can also be the temptation to push the capabilities of modelling software as far as possible, irrespective of need. An overly complex model is often unintuitive, difficult to understand and seen as a 'black box' (De Smedt, 2010). It will also run more slowly, be harder to set up appropriately, include parameters that are difficult to justify, contain buried assumptions or hidden errors, and probably function poorly in practice. Superficial explanations of an overly complex model can then appear lacking in transparency, leading to distrust of the modeller and predictions, and poor understanding of the assumptions, parameter relationships, and context of the results. By contrast, an overly simple model may help frame a problem conceptually, but deals in simplistic variables of doubtful relevance or misses out important processes. In either case, the model is unsatisfactory for use as a decision support tool and an intermediate level of complexity balancing model sophistication against simplicity (the "Medawar zone"; Grimm et al., 2005) is desirable. Even then, the variety of information sources (e.g. empirical data, heuristic knowledge and ecological rules) and numerous elements (e.g. parameters, rules, and complex interactions) can be challenging to explain.

### 4.4. Conveying uncertainty

Uncertainty in complex model predictions originates from imprecision in parameter estimates, inherent variability in the system being modelled, model structure, and uncertainty over the future scenarios for which the model is predicting a system's response (Ascough II et al., 2008; Evans, 2012). Any uncertainty over results can reduce stakeholder confidence, particularly for those unfamiliar with complex models. However, presenting uncertainty to a stakeholder in ways that are natural to a modeller, such as confidence limits of a continuous probability distribution (e.g. see Fig. 1 in Thorpe et al., 2015), could lead to false stakeholder confidence that the system's response is fully captured within the limits of this range. A probability distribution can also be difficult to translate into the discrete options a decision-maker requires (Hogarth and Soyer, 2015). For example, a '50% chance of rain' cannot translate as 'half of an umbrella'. Representing uncertainty inappropriately can contribute to peculiar decision-making behaviour such as 'decision paralysis' (the so-called Buridan's Ass paradox), or an assumption that the 'middle' option is best from a choice of three derived from a continuous spread.

### 4.5. Required communication format

The communication format and timeframe is often determined by the stakeholder audience, irrespective of the format the modeller would favour. For example, stakeholders may demand a brief written report, whereas an oral presentation including sketch graphs showing the practical implementation of the model's predictions would convey the model more effectively. When direct communication with stakeholders is limited to short, infrequent time slots, important explanations or the implications of model outputs risk being summarized to the point of irrelevance or overlooked altogether. Using technical language or failing to explain the implication of results in lay terms, is also a barrier to effective communication (Anderson, 2001), but occurs if modellers fail to correctly gauge the audience's level of technical familiarity. For example, when conveying uncertainty, stakeholders may understand the term 'uncertainty' as reflecting the modeller's lack of knowledge rather than as a genuine property of the prediction (e.g. a '50% chance of rain' could be interpreted by stakeholders as "we do not know whether it will rain or not"). If stakeholders interpret prediction uncertainty as lack of knowledge, then any technical language used to convey uncertainty risks being perceived as an attempt to conceal ignorance, thereby undermining the credibility of the model and reducing stakeholder trust. Similarly, non-scientists may struggle to understand how predictions delivering percentage likelihoods could actually be tested against empirical data, making it important to explain to stakeholders precisely how predictions were validated.

## 5. A framework for effective communication

Communication should be a controlled process of explanation and confidence-building to ensure the model outputs are understood and believed. Below, we suggest a four-stage process for communicating complex ecological models and their outputs effectively and detail the key elements to be included in Table 2. Note that the approach we propose is intended as a guide rather than a comprehensive protocol.

### 5.1. Involving stakeholders during model development

At the project outset stakeholders should be identified and consulted to pinpoint their requirements and expectations. Ideally, stakeholders should be involved throughout the modelling process, from initial planning, through multiple versions, to the final model (Fig. 2). They should help identify the practical aims and formulate the conceptual model. Any ambiguity at this stage risks the development of inappropriate models and misinterpretation of the model's outputs. Achieving consensus on the conceptual model and clarity on the practical aims increases the stakeholders' familiarity, trust and investment in the modelling process. The conceptual model should then be the basis for developing the quantitative model (hereafter, simply termed 'model').

The model will be constrained by both the stakeholders' requirements and the complexity trade-offs discussed previously. Stakeholders should help determine the degree of complexity acceptable, the entities included and the quantities to be output, and can provide key insights into parameter values and model processes unknown to the modellers, and unavailable through the scientific literature (Wood et al., 2015). Stakeholders should see the testing of each new submodel and be shown the model's foundations in established theory and the scientific literature, and its resemblance to other trusted models. By incorporating a user-friendly model interface, stakeholders can adjust parameter values themselves and see how they affect the results without needing to understand the inner workings of the model. It is true this could be a double-edged sword; stakeholders could modify model settings in order to achieve a desired result rather than seeking to answer questions appropriately. However with appropriate discussion even this can lead to increased stakeholder understanding, which is the objective during model development.

### 5.2. Preparation

When preparing to communicate a complex model to non-scientists, consider: What is the aim of the communication enterprise? What does the audience care about? How can you prepare for unexpected questions or criticism?

Communicating effectively requires understanding the stakeholder and tailoring the format to their needs. For this, consider the stakeholders' backgrounds. Do they have an agenda? What language will they understand? What narratives will resonate? What will affect their decisions? Can you prepare models of realistic scenarios relevant to these decisions and convey them in a way the stakeholder will understand? If, for example, model predictions are expressed as a probability distribution but decisions require alternative options, consider placing these options onto a continuous probability scale so stakeholders can see the associated risks (e.g. Robinson et al., 2015). Being able to simplify the predictions from a complex model will also facilitate communication. The potential for doing this will depend on the model and its purpose, but in some cases the predictions can be straightforward to communicate, even if the model itself is not. For example, stakeholders often need to know what thresholds of environmental change (e.g. climate change, habitat modification, sea level rise)

**Table 2**
Elements of complex models to communicate to non-scientist end users.

| Element | Details |
|---|---|
| 1 Model aims | - state aims at the outset<br>- ensure stakeholders not involved in commissioning work understand its rationale |
| 2 Conceptual model | - illustrate schematically<br>- justify inclusion or exclusion of key processes and elements<br>- summarize working of model indicating causes and effects<br>- provides framework for stakeholders to discuss quantitative model |
| 3 Model structure | - explain how quantitative model works<br>- present each submodel and show parameterisation<br>- demonstrate submodel and final model behaviour<br>- declare information sources<br>- explore stakeholders' alternative conceptual models as quantitative models |
| 4 Predictions | - for relevant scenarios<br>- use real numbers in formats familiar to audience<br>- translate probability distributions into options<br>- use traffic light colours (green = desired outcome; red = undesired outcome;<br>- yellow = borderline; grey = unclear)<br>- distinguish between imposed and emergent results |
| 5 Uncertainty | - be honest about reliability of predictions<br>- categorise uncertainty as data shortage, model deficiency, or 'beyond the knowable'<br>- explain qualitative uncertainty (how credible the model is, expressed descriptively)<br>- explain quantified uncertainty (expert opinion or statistical analysis of prediction<br>- uncertainty, expressed as a probability)<br>- present quantified uncertainty as confidence intervals around predictions, a continuous probability distribution, or use traffic light colours (see 4) |
| 6 Sensitivity | - show how results vary if values of input parameters are changed<br>- identify and explain processes responsible for results |
| 7 Stochasticity (if present) | - explain its role and why a stochastic model is needed |
| 8 Verification & validation | - demonstrate that submodels and final model work as intended<br>- compare model outputs to empirical data where possible |
| 9 Additional documentation | - should be sufficient to re-implement model if necessary<br>- allows stakeholders to 'zoom in' to specific detail<br>- provides quality assurance and helps establish model credibility |

result in adverse effects on ecological systems. Complex models can be used to predict such thresholds, which, along with the reasons for their variation, can be communicated to stakeholders to inform management and policy. In the management of shellfisheries for example, managers set shellfishing quotas based on the threshold amount of food required by shellfish-feeding birds, with this threshold calculated from individual-based models (Stillman et al., 2015).

If predictions require solutions beyond a business-as-usual scenario then part of the communication process requires introducing stakeholders to unexpected or novel solutions. In these cases, multiple informal discussions to familiarise stakeholders with the new ideas will be important. Finally, to anticipate criticisms and challenges it is essential to know the model thoroughly, including how the entities relate to each other, the assumptions and generalisations involved and their justification, the data used to validate the model, the specific contexts in which the model is valid, and how uncertainty can be honestly and comprehensibly presented (Mastrandrea et al., 2010; Spiegelhalter et al., 2011). Thoroughly document and justify each stage in the model and be prepared to demonstrate that you are aware of (and have incorporated) the relevant literature and expert opinion in the model.

### 5.3. Choosing communication format

Multiple communication formats help fulfil different aims. For instance, to communicate an overview of the purpose and outputs of a model, a meeting or workshop attended by relevant stakeholders, followed by a question and answer session, may be appropriate. This could include dynamic visualisations of the model (Kornhauser et al., 2009), which can be pre-recorded. Using a graphical interface as the model front end is invaluable to visualise the model behaviour as it runs (e.g. Nabe-Nielsen 2014; Fig. 3), and can show the effect of altering parameters and input values for management scenarios in real time. It can also reveal how complex dynamics emerge from interactions between individuals driven by simple rules. Experienced stakeholders can then assess whether the model responds according to their expectations. This can help resource managers understand the system they manage but crucially can also affect whether or not well-informed stakeholders believe the results.

Face-to-face meetings can be followed by informal one-to-one discussion of details. To reach stakeholders unable to attend meetings, the model can be made available for internet download with a guided tour and manual that they can explore at their leisure. Examples include 'Ecopath with Ecosim' (http://ecopath.org; Christensen and Walters, 2004), 'WaderMORPH' (http://individualecology.bournemouth.ac.uk/software.html; West et al., 2011) and 'BEEHAVE' (http://beehave-model.net; Becher et al., 2014). Graphical explanations (e.g. diagrams, animations and plots) can be incorporated into media (e.g. slides, videos, reports, or webpages) that are interpretable without the modeller necessarily present. These approaches can be supplemented with a written report describing the model, ideally peer reviewed and published with supporting information, including, for example, ODD and TRACE documents (e.g. Johnston et al., 2014).

### 5.4. Evaluating effectiveness

Evaluating communication effectiveness has received little formal attention, yet the degree to which communication is effective ultimately governs the relevance and societal impact of the model. At present there is little understanding of what constitutes effective communication with stakeholders, let alone how to measure it. For example, does effectiveness require that the audience understands and uses the information being delivered, or simply that they were engaged in the communication process? To what extent is it the modeller's responsibility to ensure that the audience understands?

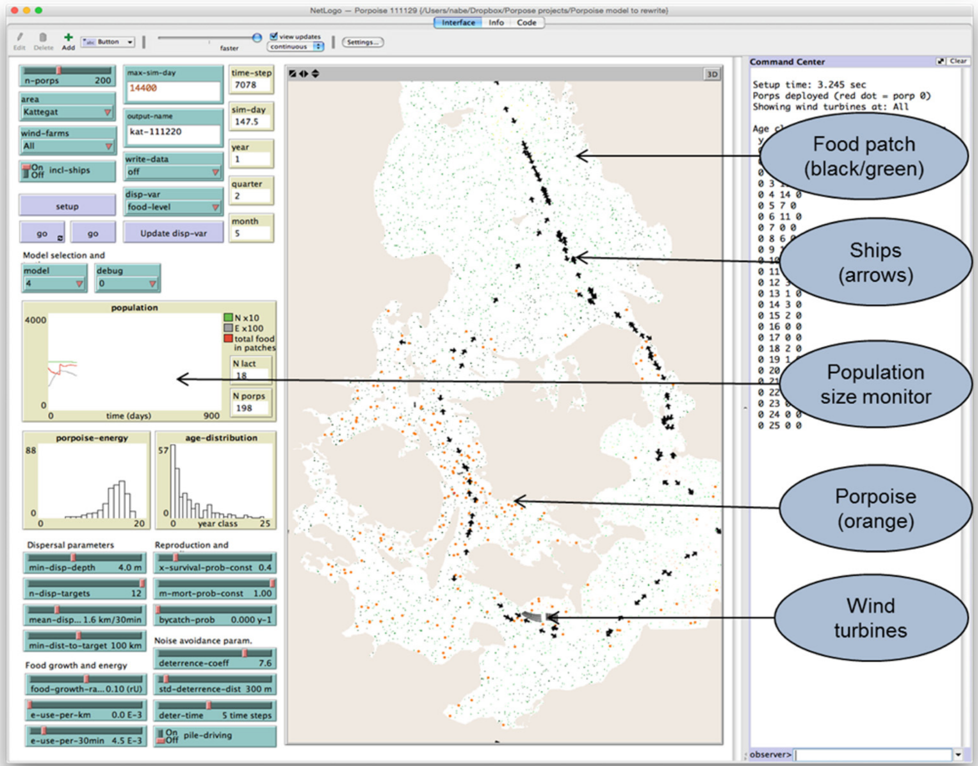


**Fig. 3.** Visualising and interacting with a complex ecological model. There are multiple options for conveying model dynamics to non-scientist end users. One option is to allow stakeholders to interact with and interrogate the model themselves by altering parameter values via a user-friendly model interface. The figure shows the *NetLogo* interface for an IBM predicting how harbour porpoise behaviour and population size is affected by cumulative anthropogenic disturbances (existing wind turbines, new turbine developments, shipping noise, and by-catch) from Nabe-Nielsen et al. (2014).

We propose three criteria for judging whether communication of a complex model and related outputs is effective: (1) Does the stakeholder subsequently have enhanced knowledge of the model and its relevance? (2) Does the model affect subsequent management decisions? And (3) does the behaviour of the system being modelled consequently improve? To illustrate, climate change science carried out by the Intergovernmental Panel on Climate Change has achieved the first and second criteria, whereas the science of ozone depletion appears to have achieved all three (Ungar, 2000).

At early stages in the process it may only be appropriate to measure effectiveness based on criterion 1. A stakeholder survey could be an objective means of measuring this, but in our experience this is generally impractical to implement. One immediate, qualitative measure is the intensity of discussion following direct communication such as presentations. Lengthy discussion and lots of questions suggests the audience was engaged and cares about the information presented. However silence following a presentation is not necessarily bad and may in fact be a necessary step, particularly when stakeholders are exposed to novel modelling methods. In such cases, only repeated communication using a variety of formats will break down any ‘black box’ barrier to stakeholder engagement.

It may be many years before evaluation according to criteria 2 and 3 is appropriate. Even then, it will be challenging to assess whether the model’s impact on a management decision is related to how the model was communicated. For example, ecological models commissioned as part of the 30-year Comprehensive Everglades Restoration Plan in Florida, USA (“ATLSS”, DeAngelis et al., 1998; “ELM”, Fitz et al., 1996) were at the time considered to be too complex and their uncertainty too great to be relied upon for decision-making (Sklar et al., 2001), and of these models only ELM was subsequently formally approved and used in planning for aquifer restoration in the region (Orem et al., 2014).

## 6. Conclusions

The predictions of complex models are used as evidence to develop operational advice, assist decision-making and regulation, and guide management strategies. Therefore models and their predictions must be communicated effectively to end users if they are to be interpreted correctly and used appropriately. In this review we have proposed a general approach to the communication process and highlighted the key elements that should always be conveyed. However, this is not a comprehensive guide and given the increasing popularity of complex models in ecology we suggest this area warrants more attention. At the least, the take-home message from this synthesis is that communication is not simply a one-way transmission of information from the modeller to their intended audience; but rather, it is an iterative, engaged process in which both the science and the stakeholders benefit from exchanges of information. Modellers moving into applied research can learn from climate science, risk assessment and the established communication strategies used in industry and advisory bodies. Looking ahead, better measures of the effectiveness of communication between modellers and stakeholders are needed to help increase the impact of complex models in ecology.

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